Probabilistic Precipitation Nowcasting with the Short-Term Ensemble Prediction System in Belgium

Loris Foresti

Radar and Lightning Detection group,
Royal Meteorological Institute of Belgium, Brussels

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PLURISK objectives

- Quantification, forecasting, warning, control and management of urban pluvial floods
- Typical response times of urban catchments and sewer systems: 10-60 minutes
- PLURISK WP1: nowcasting
  - Nowcasting of fine-scale extreme rainfall using C-X band radar data, NWP outputs and lightning data
  - INCA-BE system provides deterministic nowcasts
  - Probabilistic nowcasting from an ensemble of scenarios?
  - High resolution and frequently updated ensemble rainfall nowcasting not possible with NWP

	Nowcasting	NWP ALARO
Spatial resolution	1-2 km^2	4 km^2 x 5
Temporal resolution	5-10 min	1 hour
Update cycle	5-10 min	6 hours
Computing time	< 5-10 min	4 hours (+spin-up)

Ensemble/probabilistic nowcasting?

- Nowcasting: very-short term forecasting of weather (0-6h)

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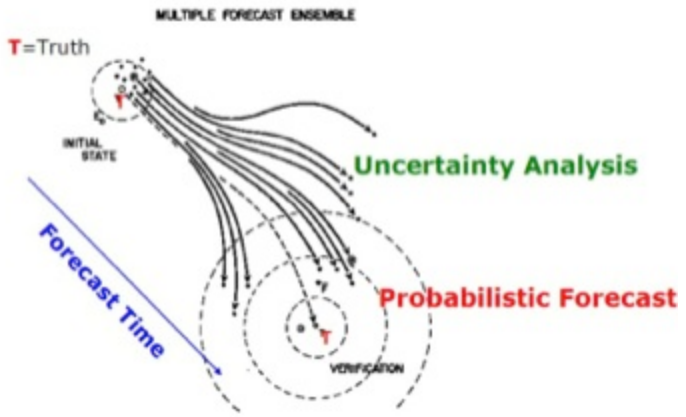
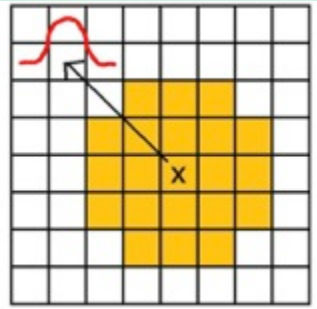
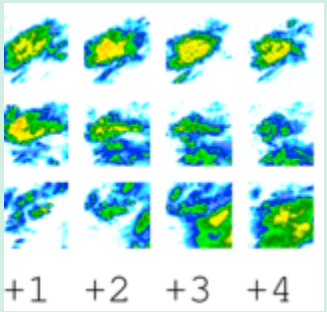
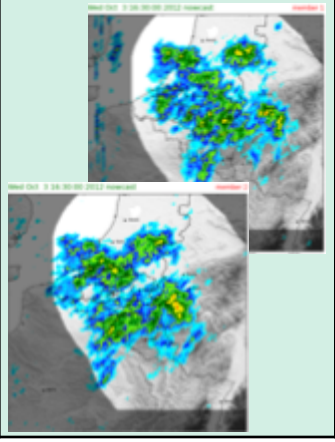
- Nowcasting of precipitation strongly driven by the extrapolation of radar images
- The INCA-BE nowcasting system at RMI provides deterministic precipitation nowcasts

  => what is the forecast uncertainty?

- Ensemble nowcast: possible set of weather scenarios
- Probabilistic nowcast: proportion of the ensemble exceeding a given threshold

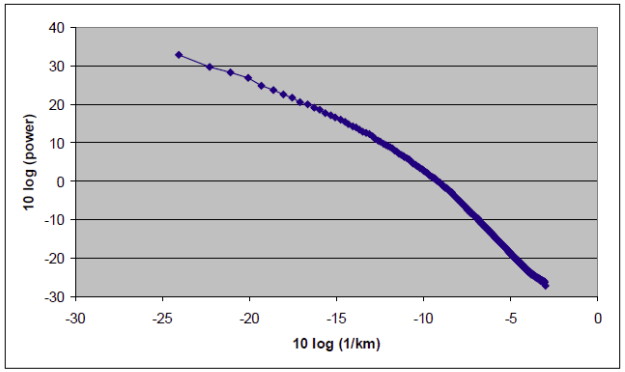


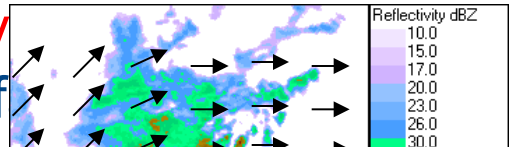
Heuristic probabilistic rainfall nowcasting

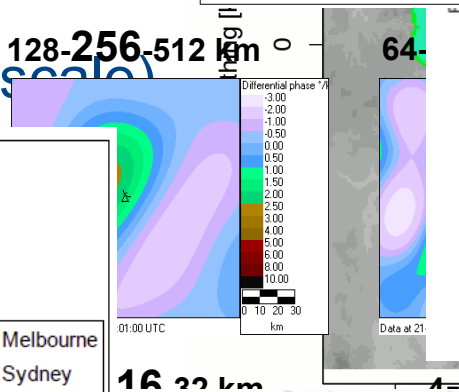
Approach		Pros	Cons
Deterministic nowcast post-processing Raincast (Schmid et al., 2000) MAPLE local Lagrangian approach (Germann and Zawadzki, 2003)		- No need to explicitly generate ensembles - Easy to implement on deterministic systems	- Underestimation of forecast uncertainty - Non-independent "ensemble members"
Analogue approach Radar sequence retrieval (Otsuka et al., 2000) NORA (Panziera et al., 2012; Foresti et al., 2013)		- Analogues have good space-time properties - Better uncertainty quantification	- Low forecast skill (no Lagrangian persistence) - Extreme events never seen before?
Stochastic approach Space-time multifractals (Marsan et al., 1996; Macor et al., 2006) S-PROG (Seed, 2003) STEPS (Bowler et al., 2006); SBMcast (Berenguer et al., 2013)		- Elegant statistical framework - Exploits Lagrangian persistence - Independent and equally likely ensemble members	- Mathematical complexity of some models - Need to integrate more meteorological knowledge

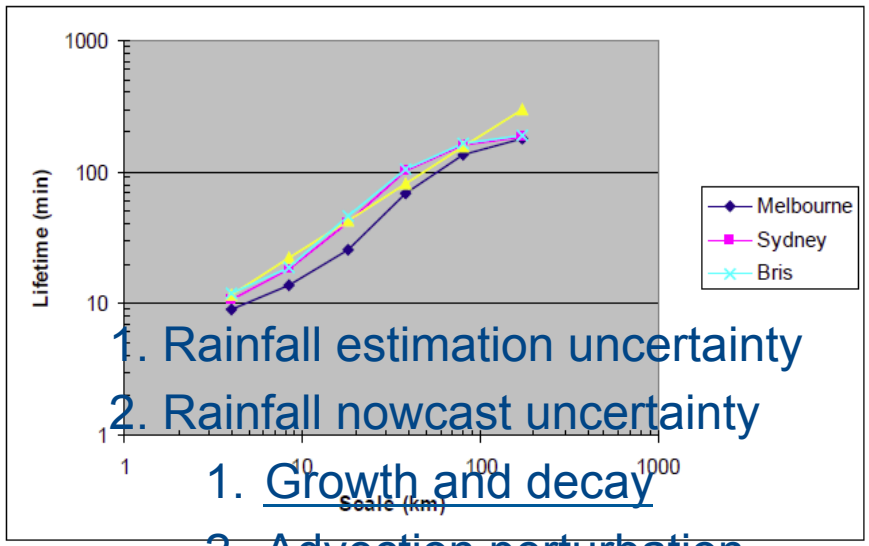
Short-Term Ensemble Prediction System

1. Estimation of advection using optical flow on radar images
2. Spatial scaling (FFT decomposition of rain field)
3. Dy
(rainf



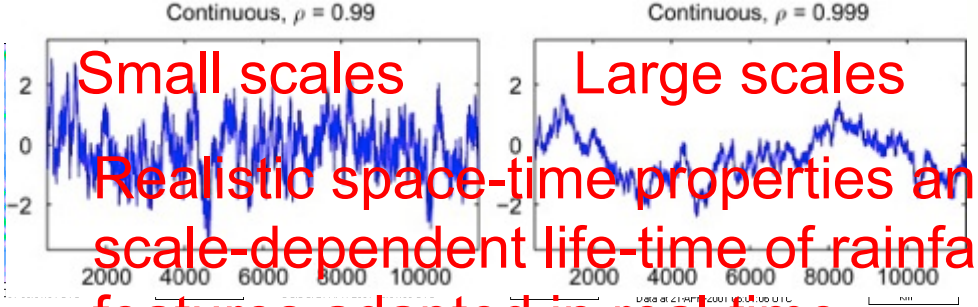






1. Rainfall estimation uncertainty
2. Rainfall nowcast uncertainty
   1. Growth and decay
   2. Advection perturbation
   3. Broken line model for mean areal rainfall

Lovejoy et al., JGR, 1987

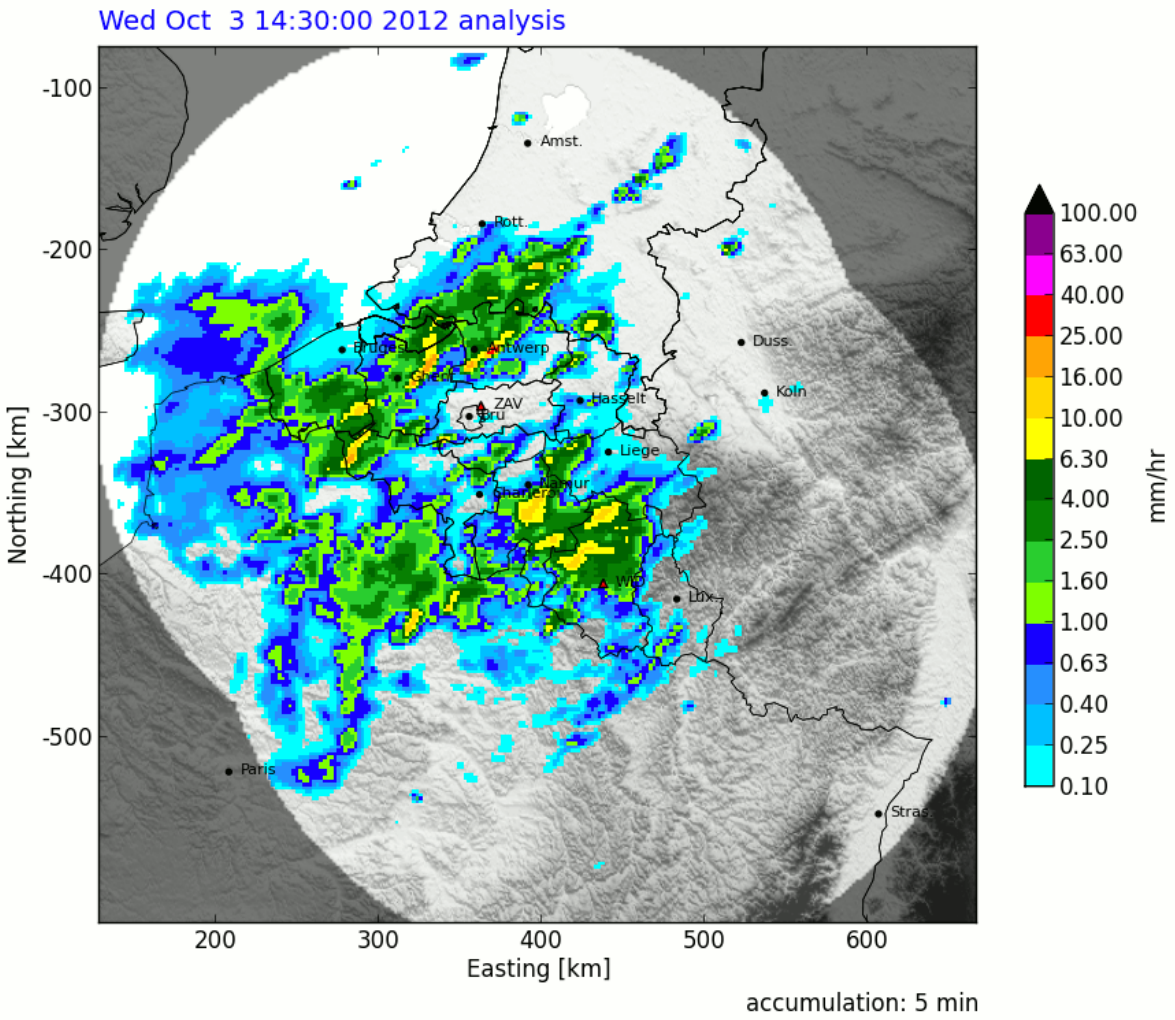


Small scales

Large scales

Realistic space-time properties and scale-dependent life-time of rainfall features adapted in real-time

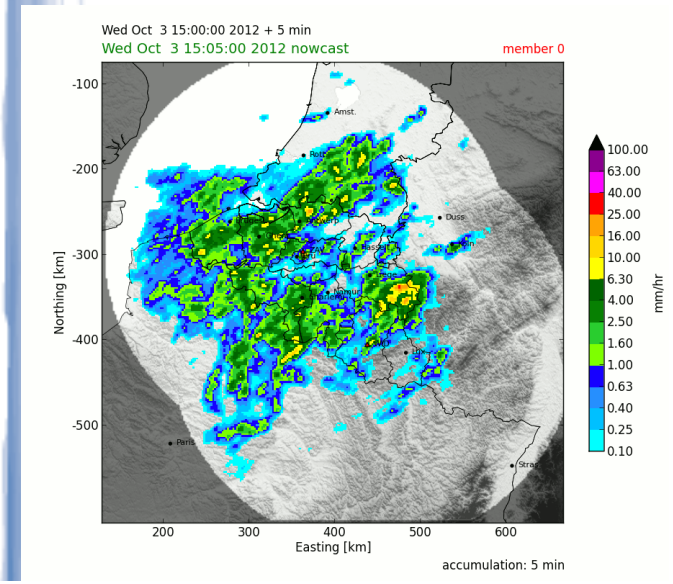
STEPS stochastic nowcast

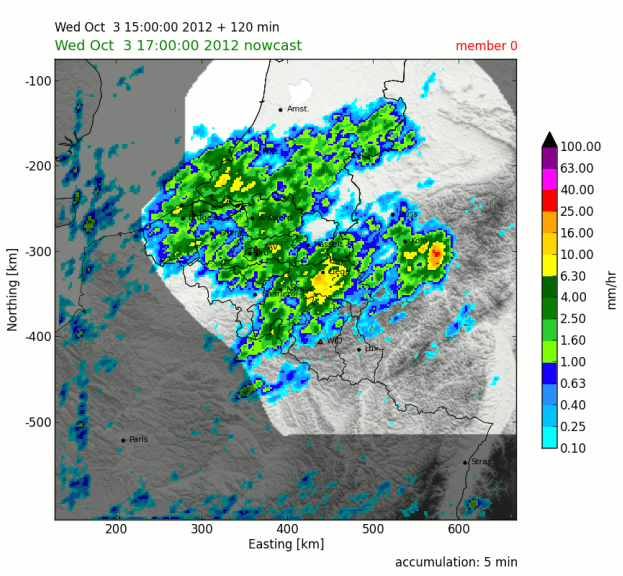


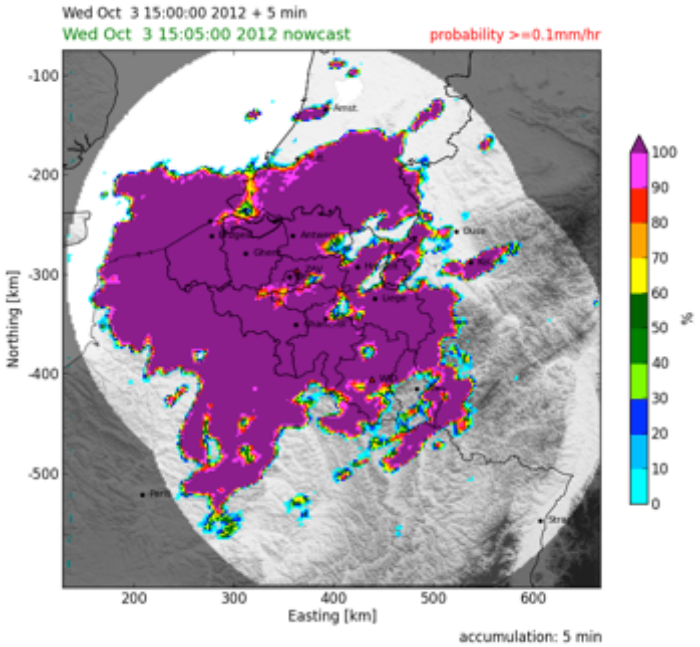
- 20 stochastic ensemble members
- Observation and forecast uncertainty

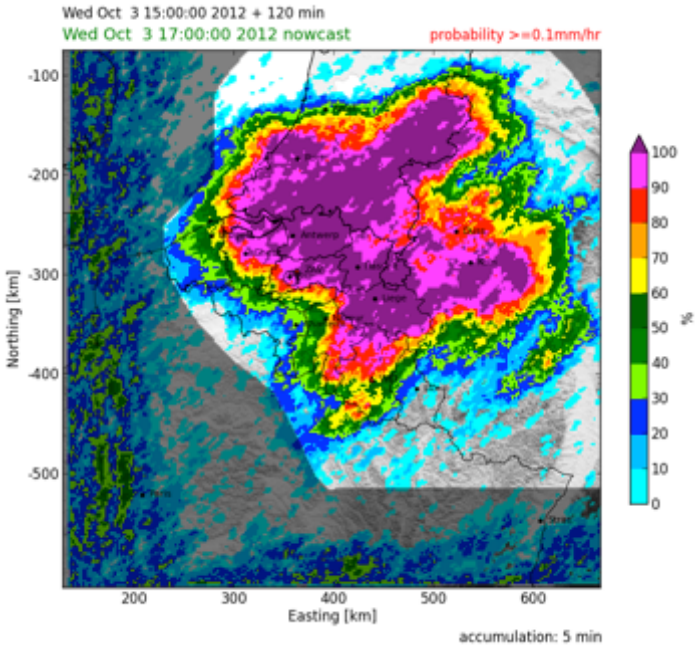
- Analysis = radar observations = quantitative precipitation estimation (QPE)
- Nowcast = radar extrapolation = quantitative precipitation forecast/nowcast (QPF/ QPN)

STEPS probabilistic nowcast



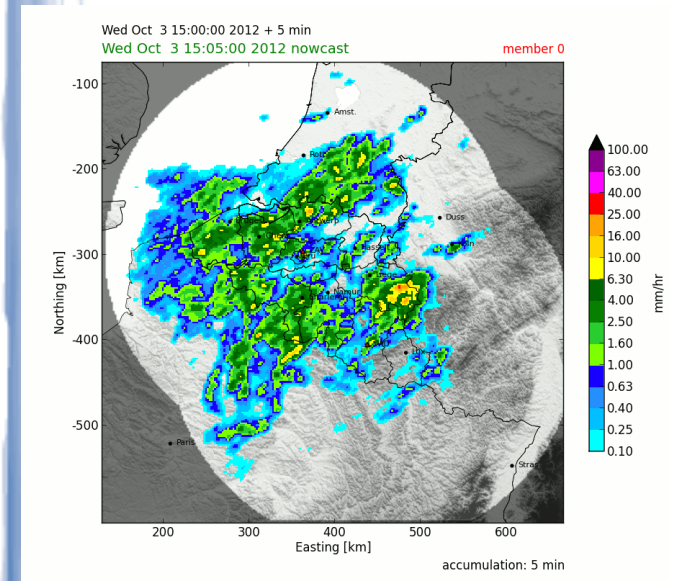


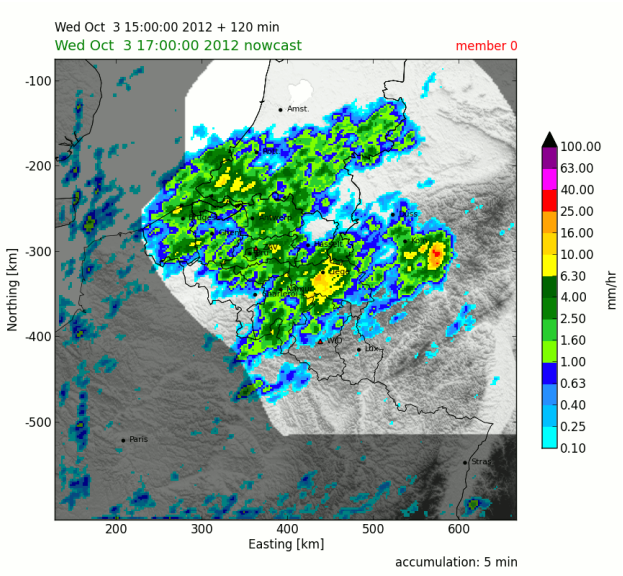


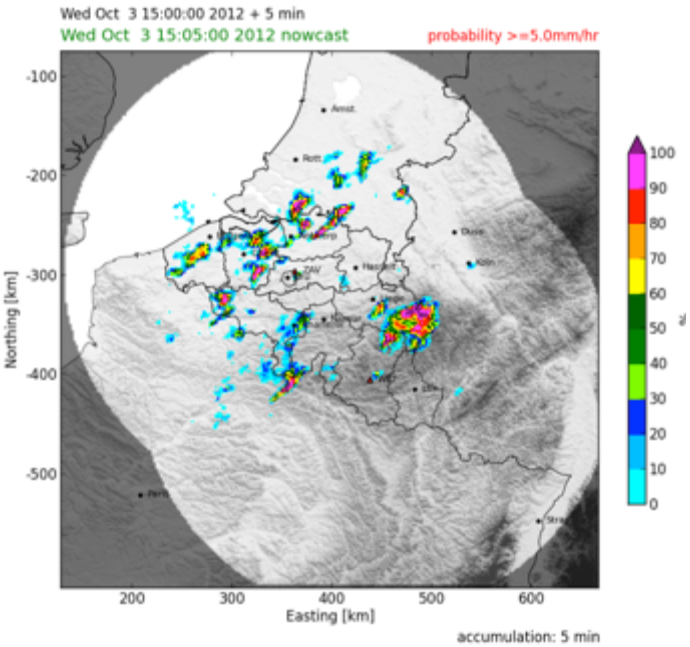


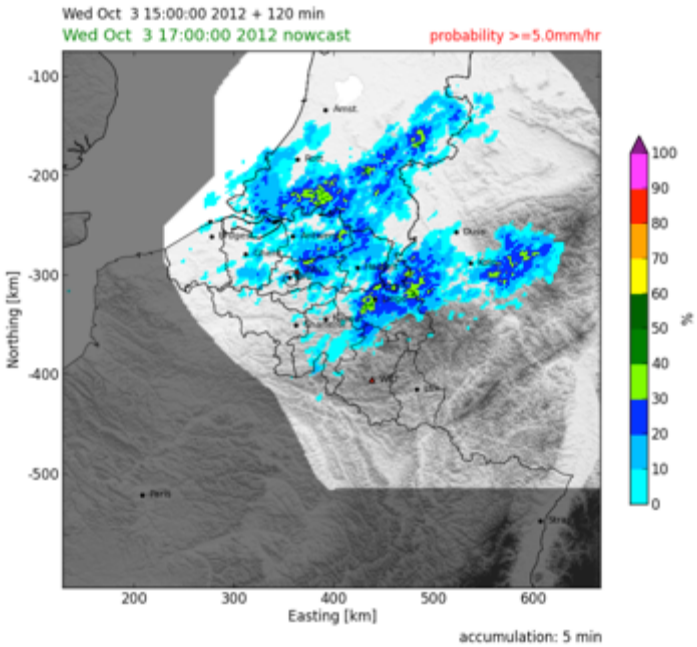
% ensemble members >= rainfall threshold (equivalent 0.1 mm/hr)

STEPS probabilistic nowcast





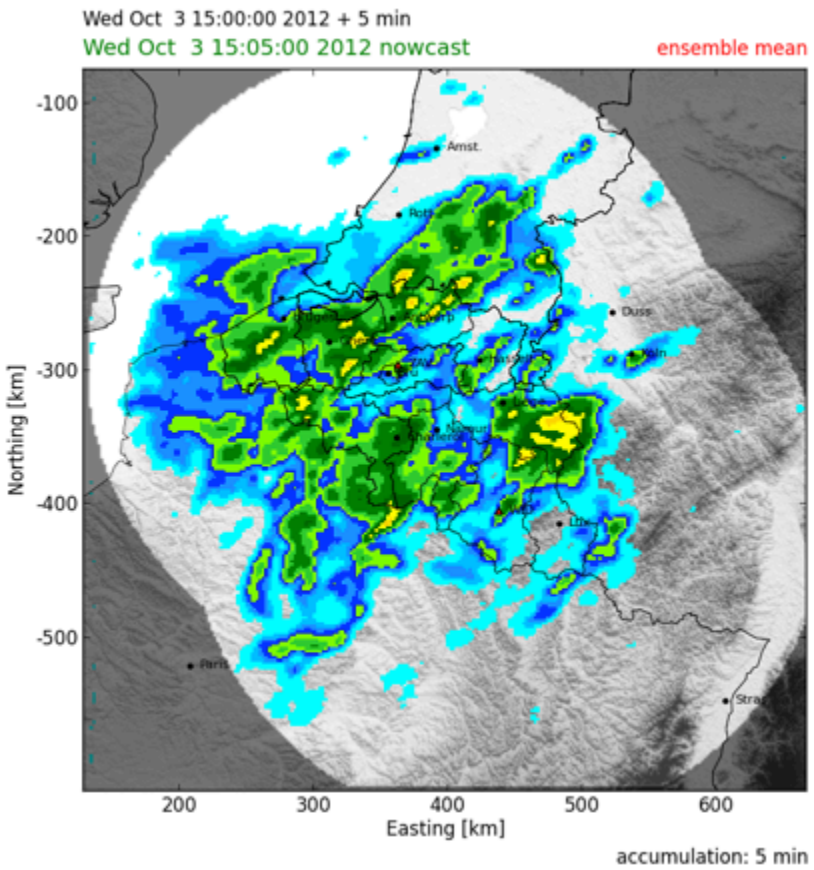


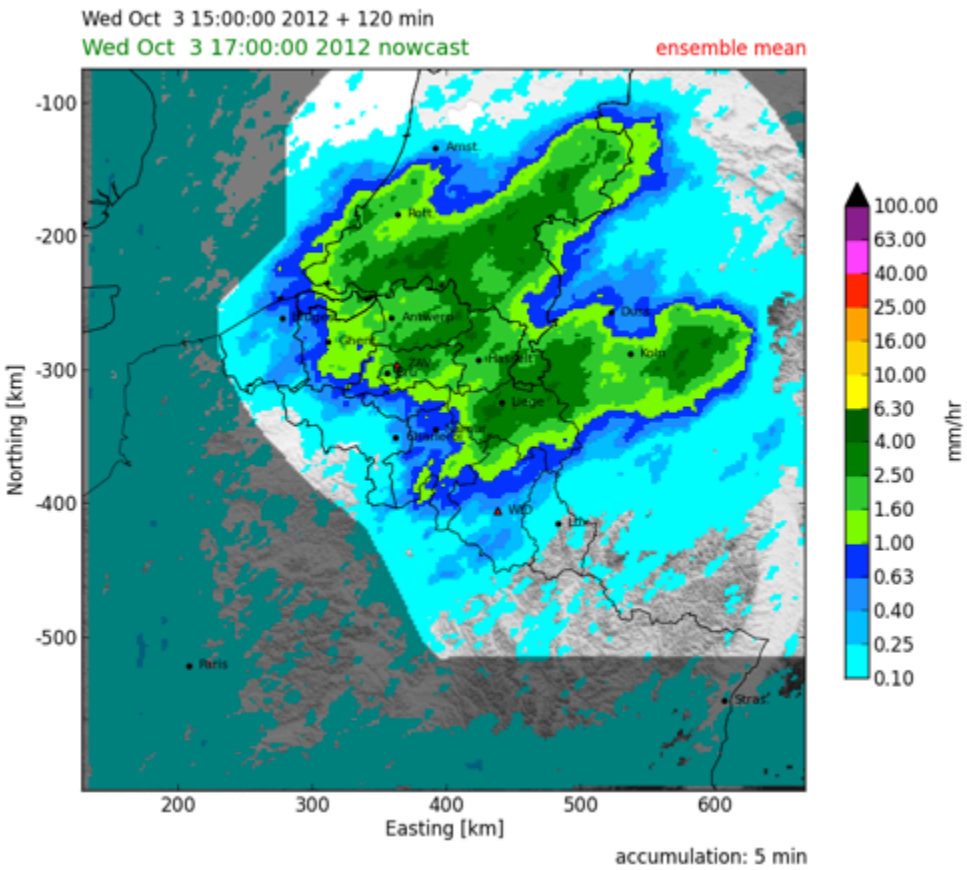


% ensemble members >= rainfall threshold (equivalent 5.0 mm/hr)

STEPS ensemble mean

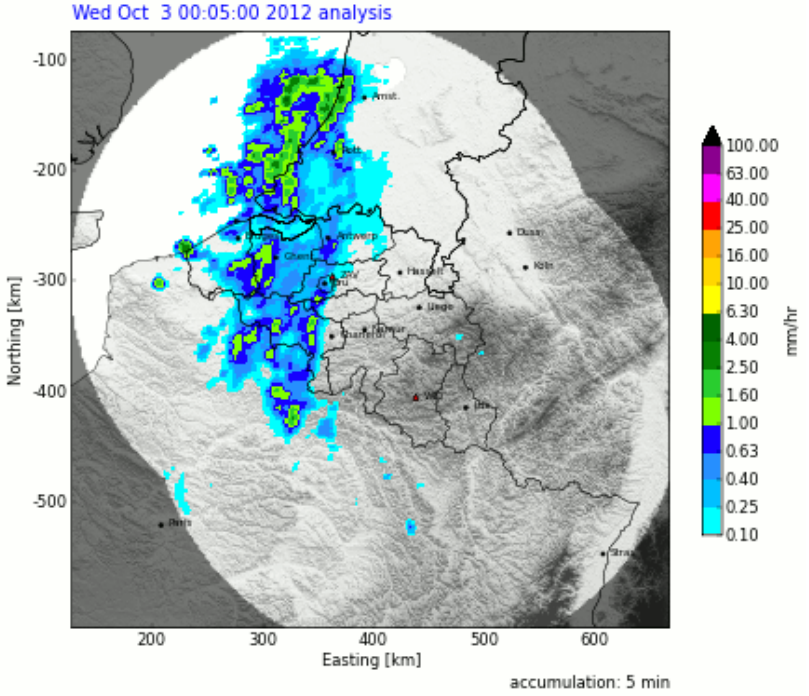
- Average of ensemble members
- "Deterministic" quantitative rainfall nowcast
- Accounts for loss of predictability (unpredictable features are smoothed out)





PLURISK case study: 3 October 2012

- One nowcast issued every 5 minutes over the day (total = 288 ensemble nowcasts)
- 256x256 domain at 2x2 km^2 spatial resolution
- Nowcast of 5 and 30 minute rainfall accumulations up to +2 hours lead time
- Roughly 1-2 minutes computational time per nowcast



Forecast verification

Why verify?

- Monitor forecast skill over time
- Diagnose forecast errors
- Compare different models
- Predict the forecast accuracy

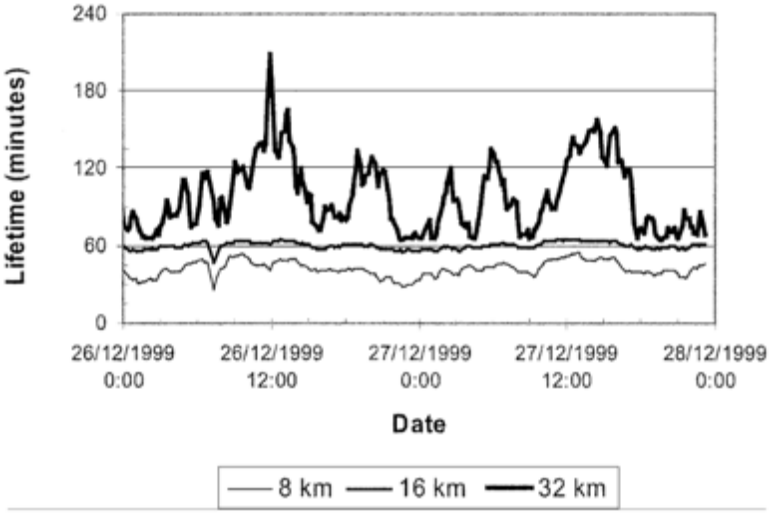
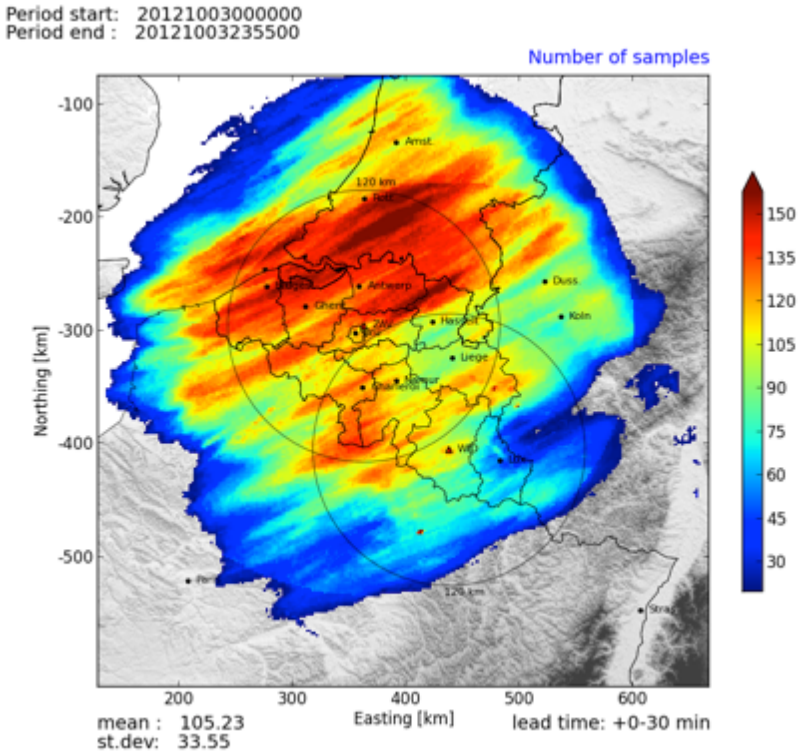
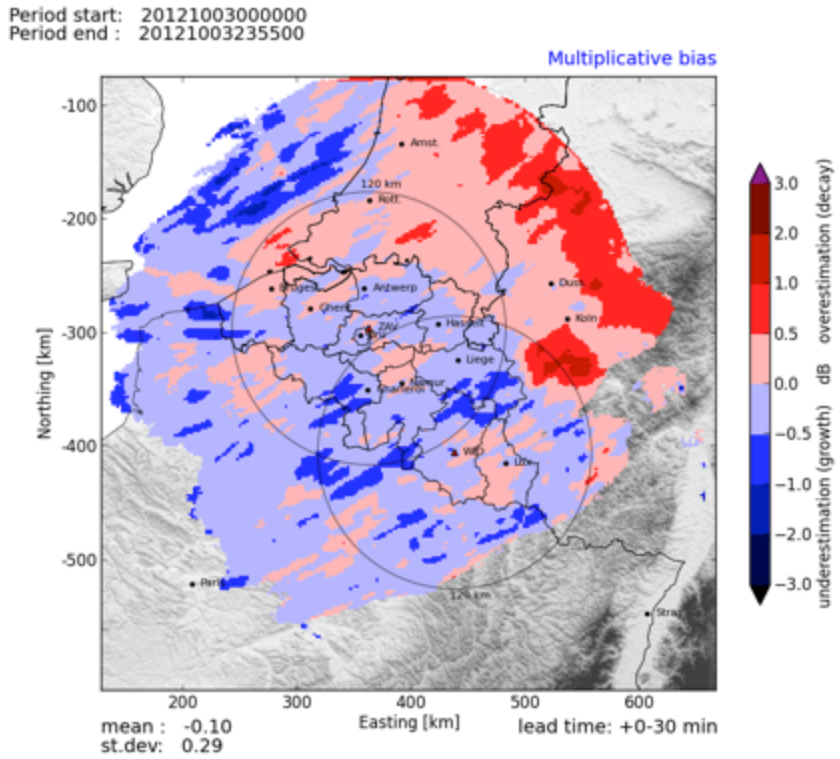


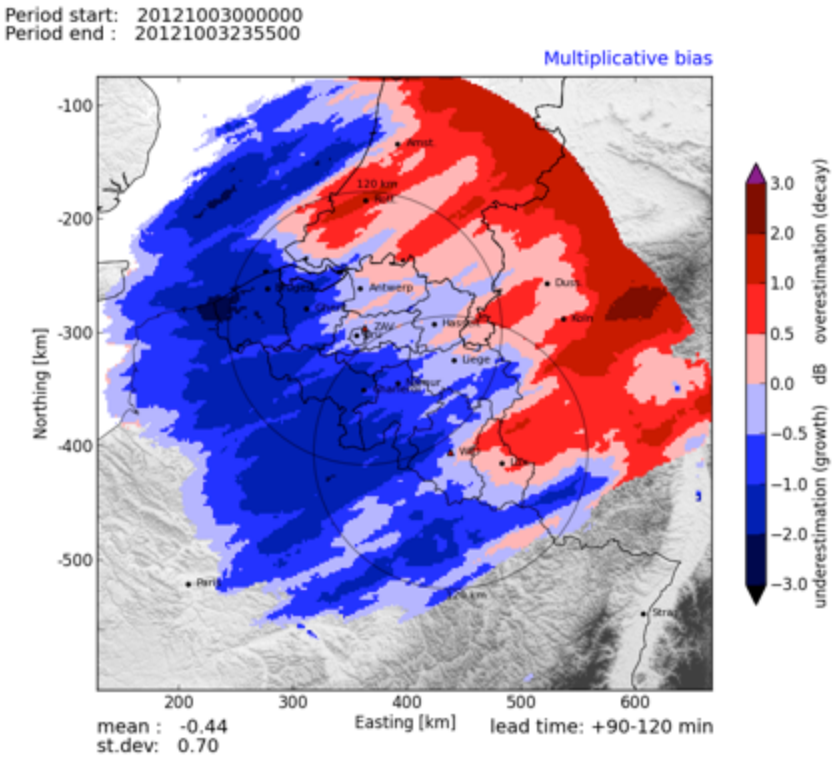
FIG. 7. Time series of the Lagrangian autocorrelation lengths for 8-, 16-, and 32-km-scale structures.



- Forecast errors are highly variable in space and time
- Number of samples is much higher in space (nr. pixels) than time (nr. time steps / forecasts)

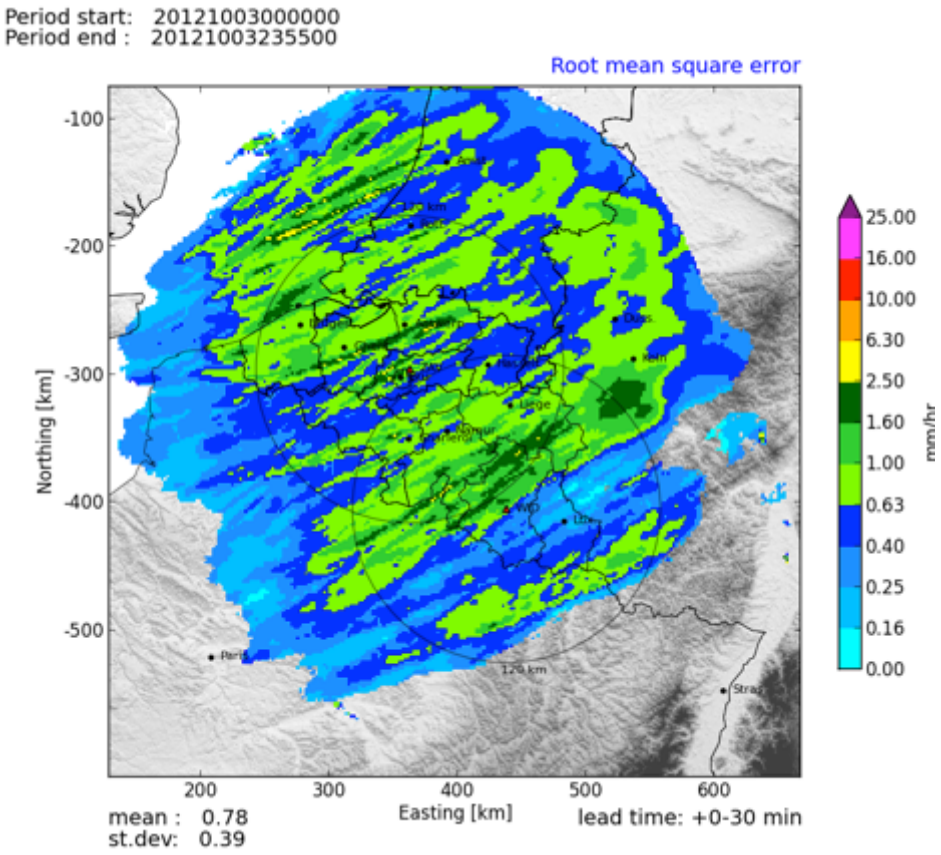
Continuous verification (bias)

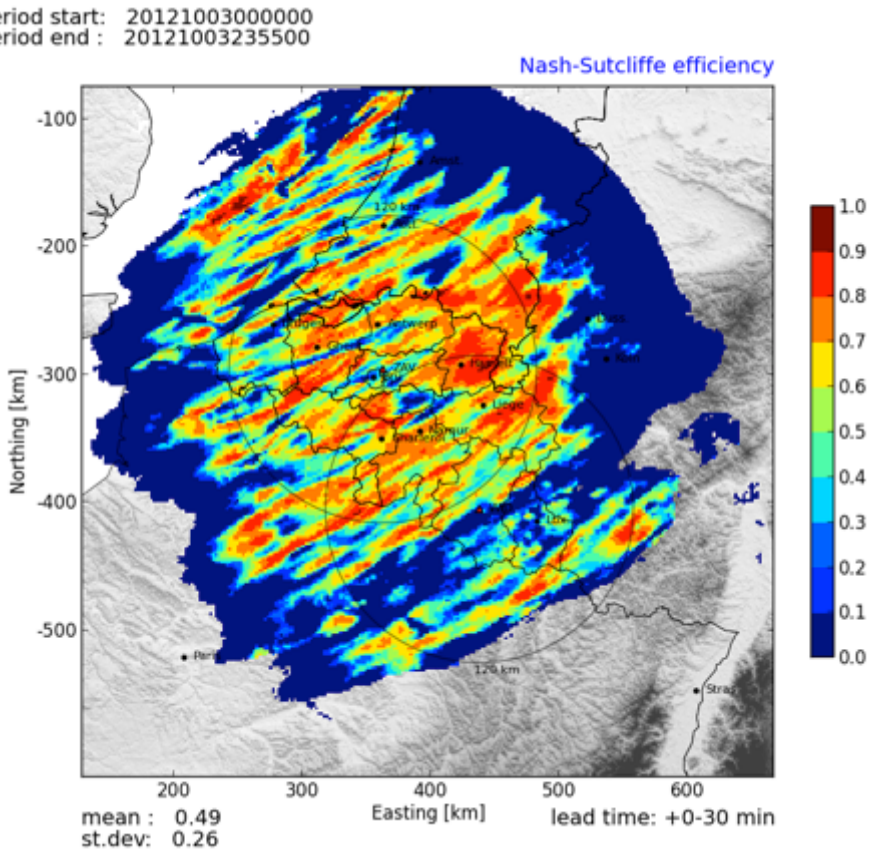




$$\text{Multiplicative bias} = 10log_{10}\left(\frac{Forecast + 2\,mm\,hr^{-1}}{Radar + 2\,mm\,hr^{-1}}\right)$$

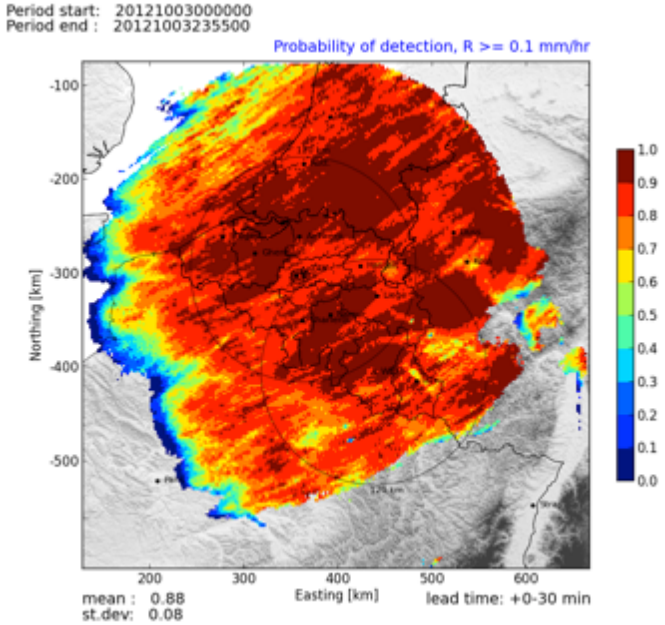
Continuous verification (Nash-Sutcliffe)

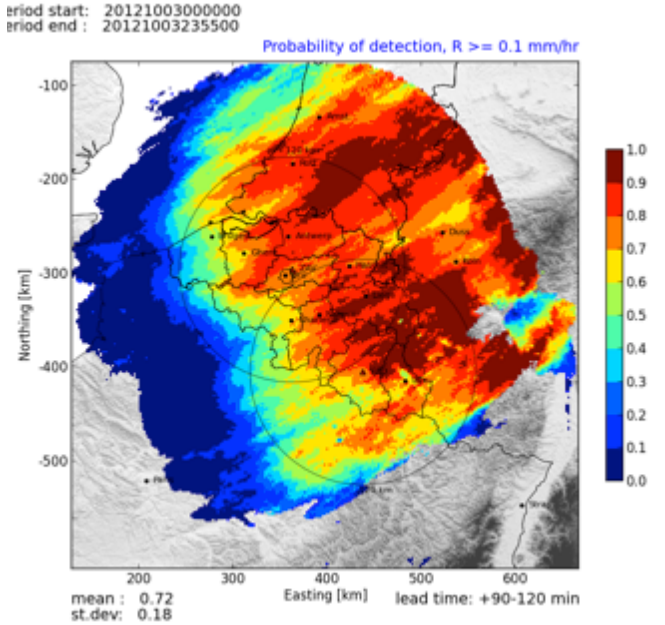




$$\text{Nash-Sutcliffe efficiency} = 1 - \frac{RMSE\{Forecast, Radar\}}{Var\{Radar\}}$$

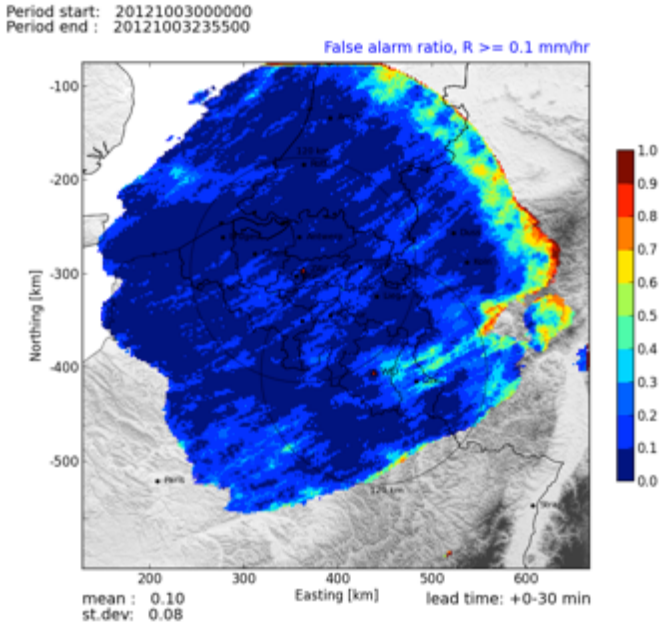
Categorical verification (POD-FAR)

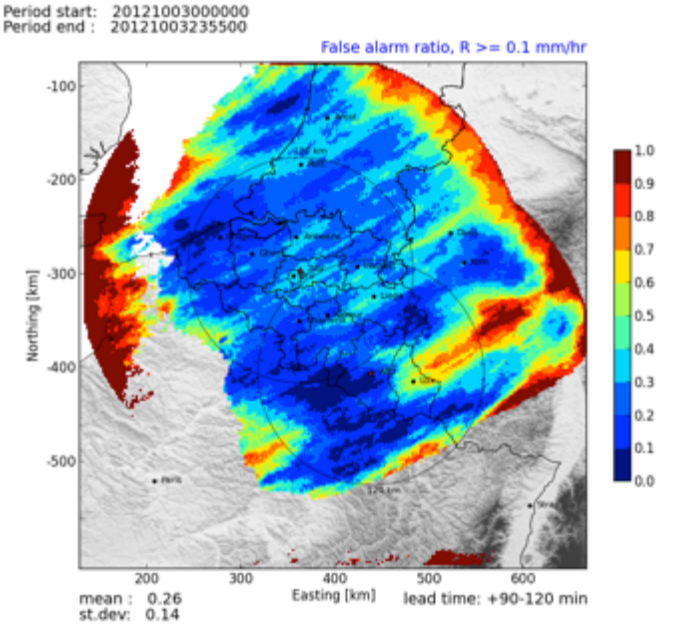




$$POD = \frac{hits}{hits + misses}$$

- What fraction of the observed events was correctly forecast?

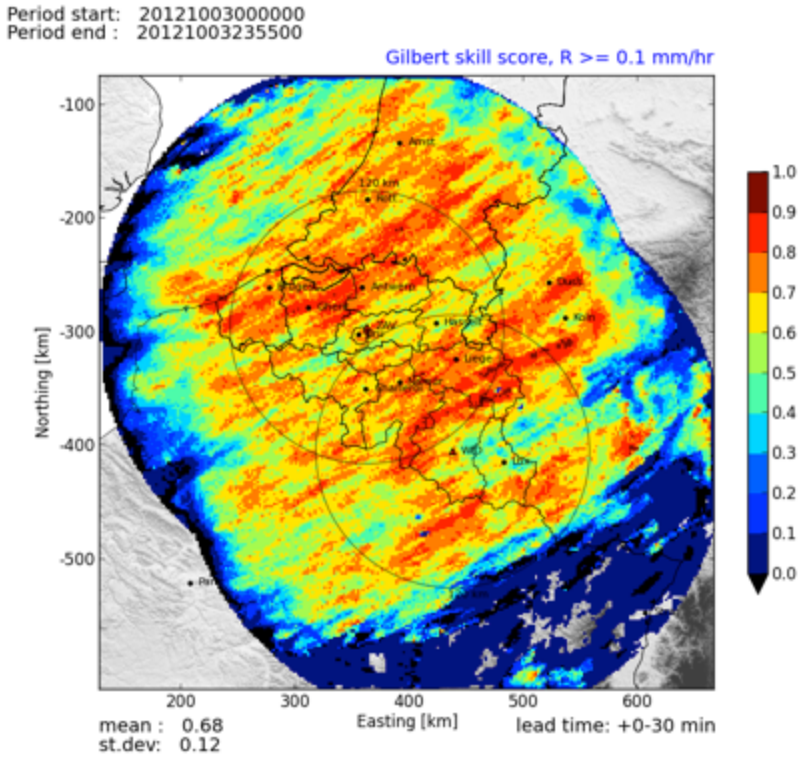


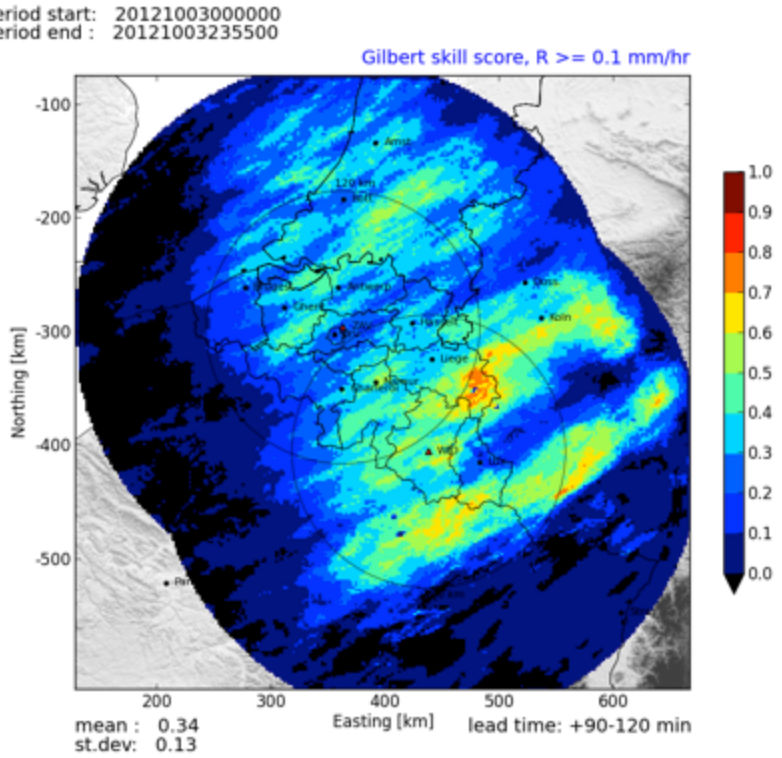


$$FAR = \frac{false\ alarms}{hits + false\ alarms}$$

- What fraction of forecast events actually did not occur?

Categorical verification (GSS)

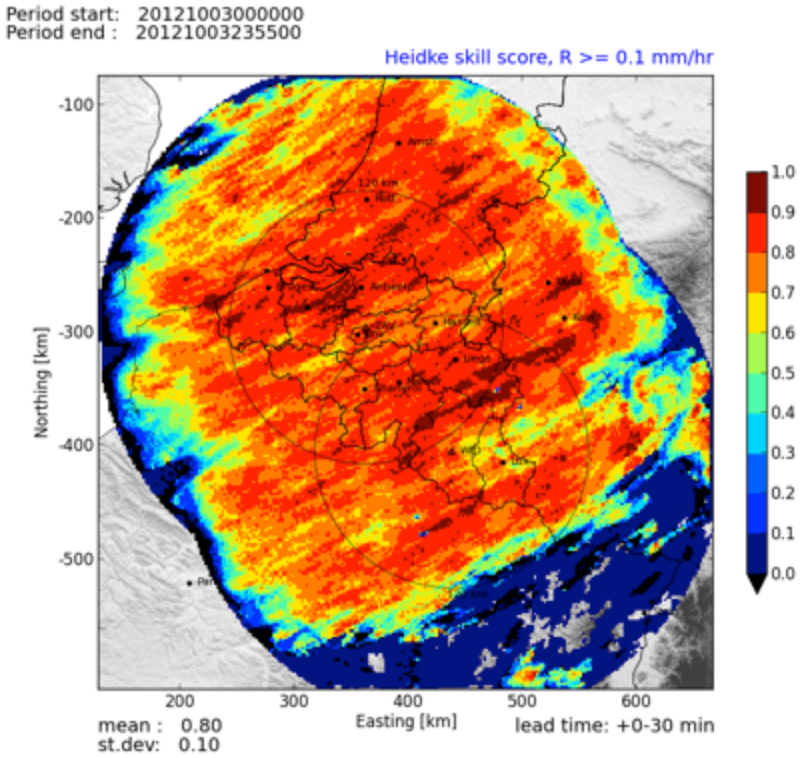


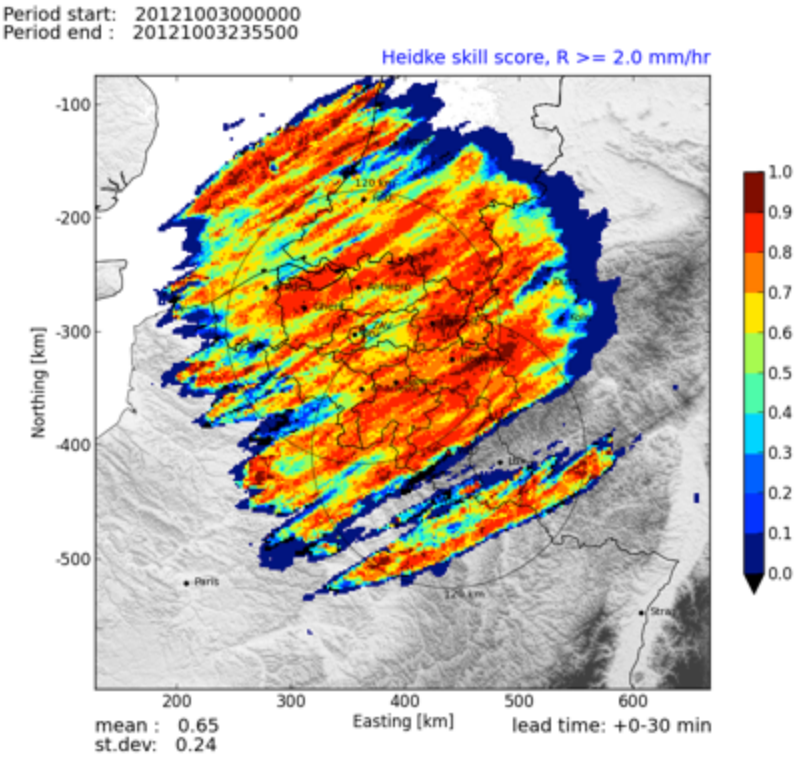


$$ETS = \frac{hits - hits_{random}}{hits + misses + false\ alarms - hits_{random}}$$

- GSS = Gilbert Skill Score = ETS = Equitable Threat Score
- How well did the forecast events correspond to the observed events (corrected by random chance)?

Categorical verification (HSS)

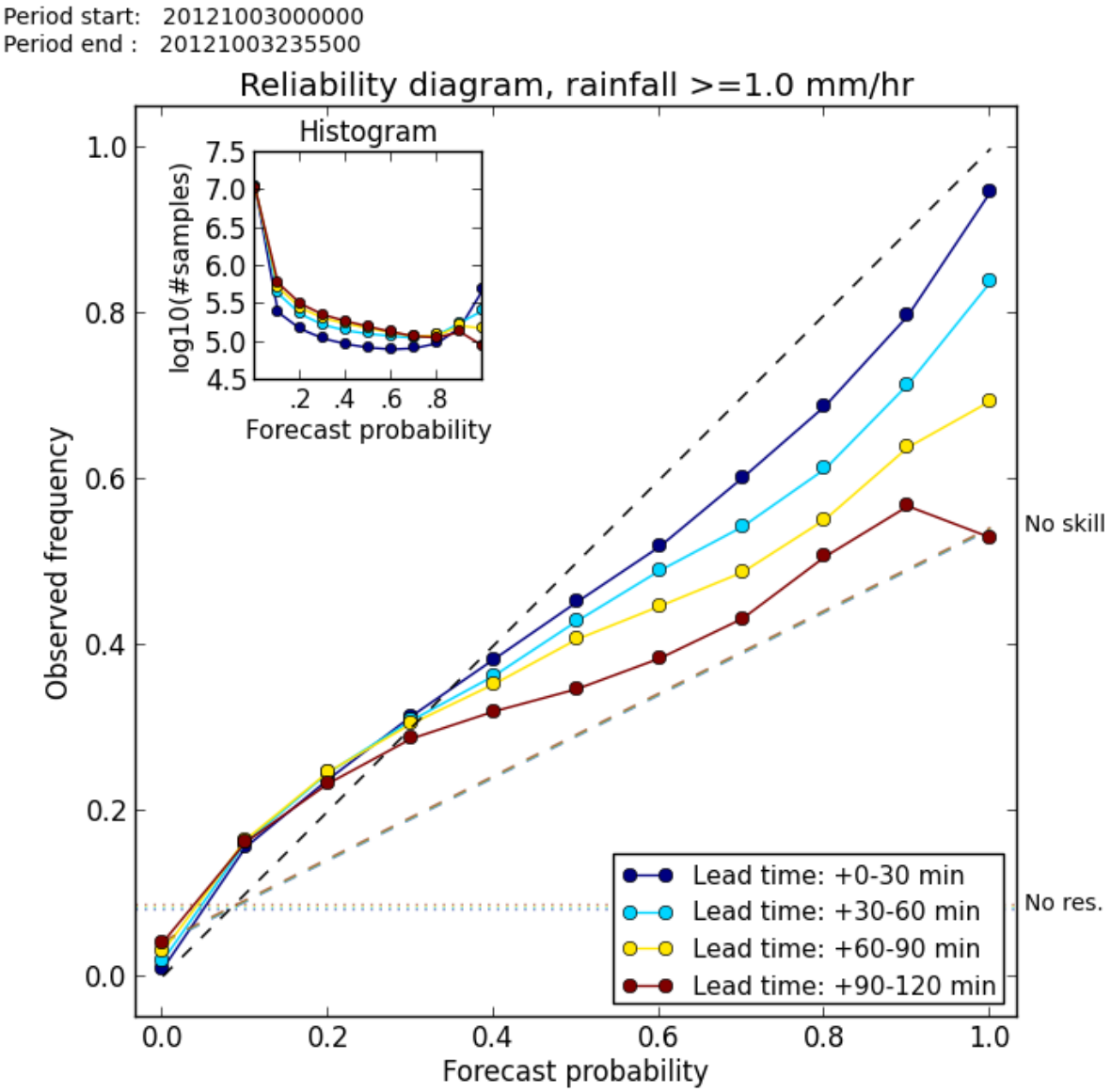




$$HSS = \frac{(hits + correct\ negatives) - (expected\ correct)_{random}}{N - (expected\ correct)_{random}}$$

- HSS = Heidke Skill Score = Cohen's kappa index
- What was the accuracy of the forecast compared with random chance (both events and non-events)?

Probabilistic verification (Reliability)

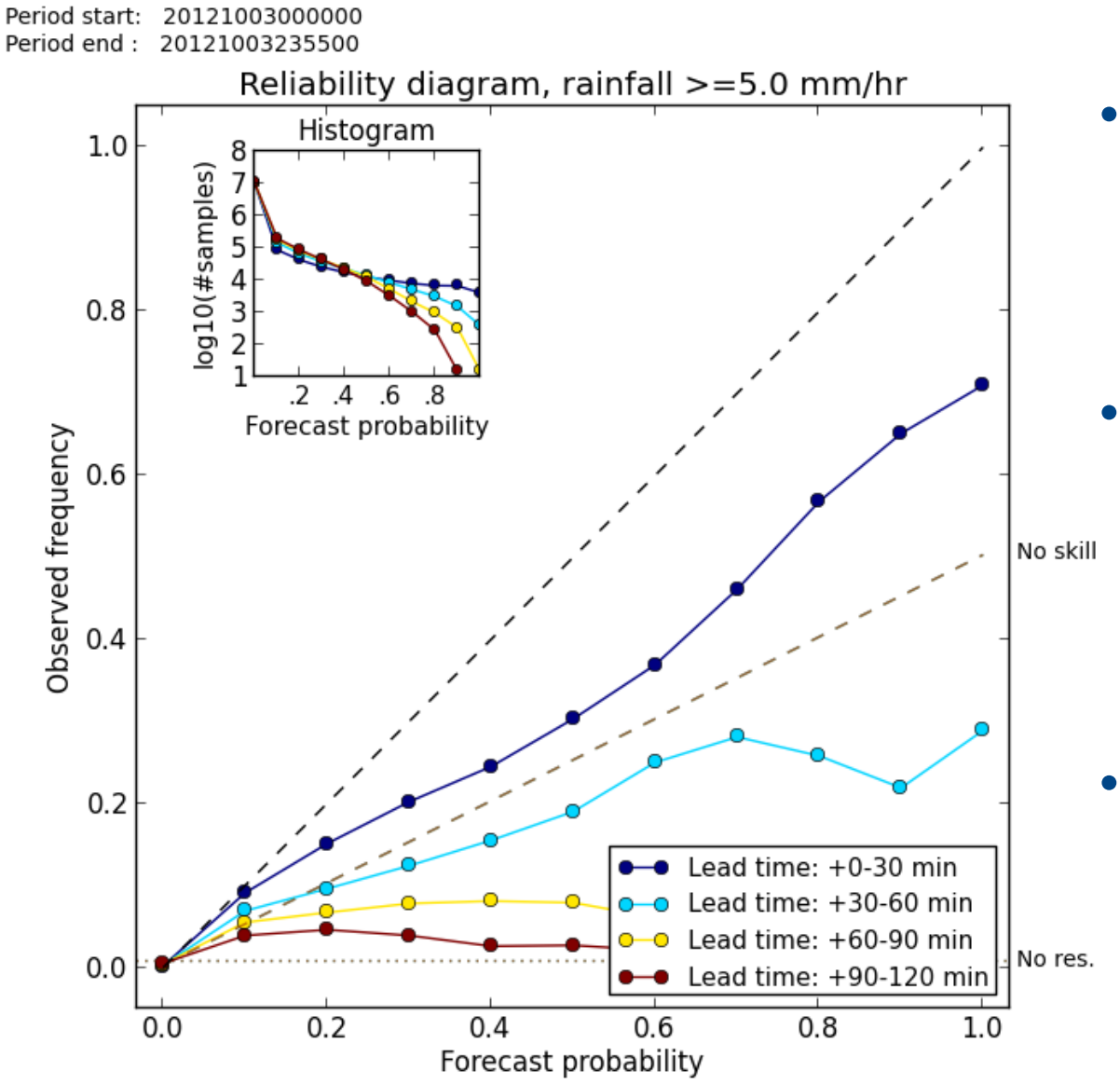


Reliability: agreement between forecast probability and observed frequency

Resolution: ability of the forecast to distinguish situations with strictly different observed frequencies

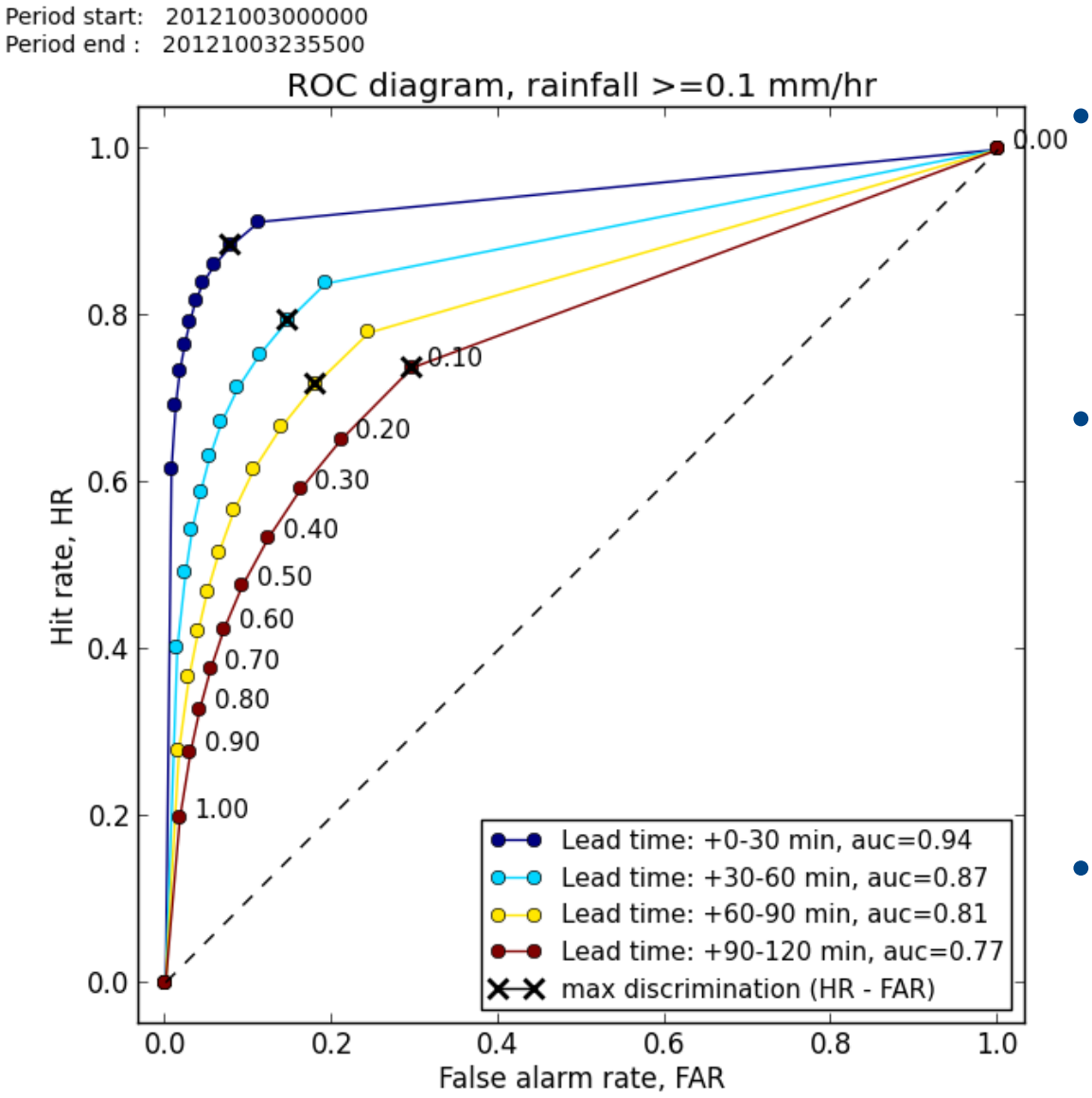
Sharpness: ability to forecast probabilities near 0 or 1

Probabilistic verification (Reliability)



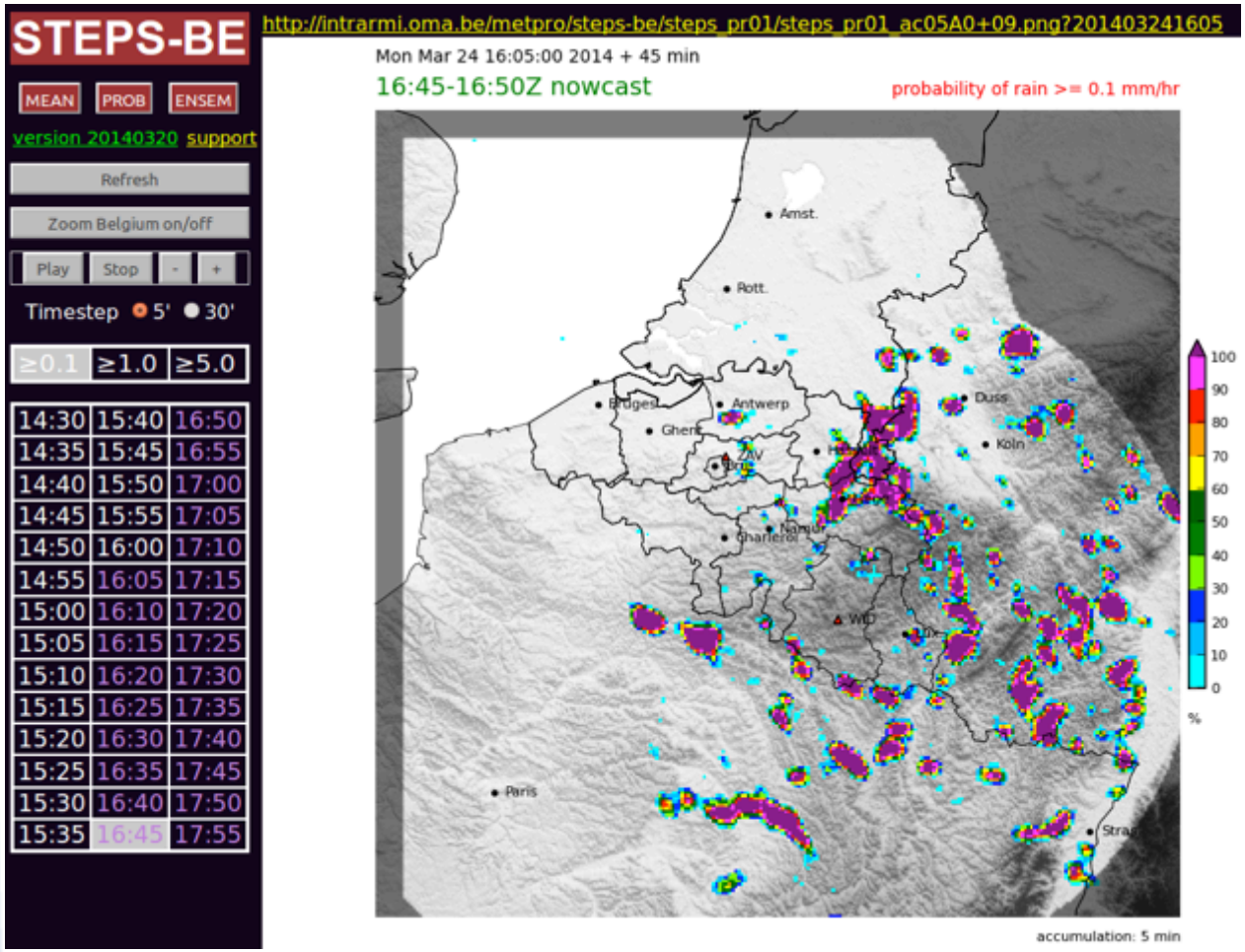
- Reliability: agreement between forecast probability and observed frequency
- Resolution: ability of the forecast to distinguish situations with strictly different observed frequencies
- Sharpness: ability to forecast probabilities near 0 or 1

Probabilistic verification (ROC)



- Discrimination: ability of the probabilistic forecast to discriminate between events and non-events
- *Hanssen and Kuipers discriminant (Peirce's skill score): maximization of hits and minimisation of false alarms*
- *Area under the ROC curve*

Next STEPS…

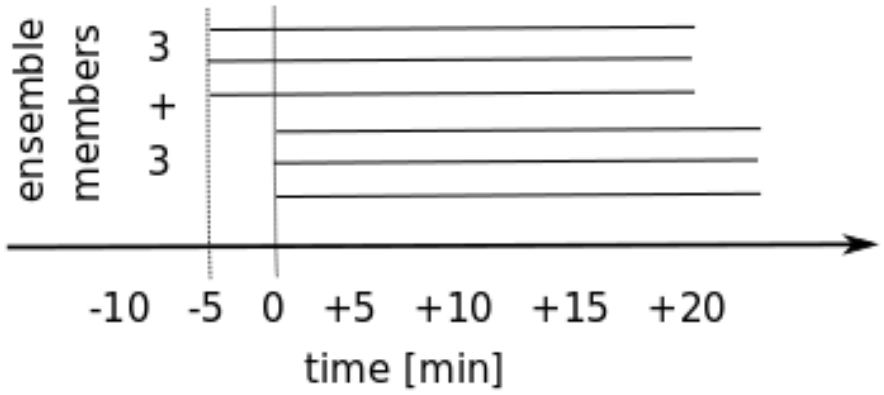


- Real-time test
- Running case studies on re-analyzed radar archive (ground clutter and VPR correction)

- Rain gauge calibration of the multiscale QPE ensemble
- Ensemble rainfall QPE/QPF => ensemble hydrological nowcasts. Added value?

Beyond the next STEPS

- Multiscale velocity field estimation
- Spatial and temporal variability of cascade parameters
- Integration of growth and decay via bias correction
- Time-lagged ensemble members for probabilistic nowcasting



References

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  - Norman, K., A. Seed, and C. Pierce (2010), A comparison of two radar rainfall ensemble generators, paper presented the Sixth European Conference on Radar in Meteorology and Hydrology (ERAD 2010), Administratia Nationala de Meteorologie, Sibiu, Romania.
- STEPS
  - Seed, A. W. (2003), A dynamic and spatial scaling approach to advection forecasting, J. Appl. Meteorol., 42, 381–388.
  - Bowler, N., C. E. Pierce, and A. W. Seed (2004), Development of a rainfall nowcasting algorithm based on optical flow techniques, J. Hydrol., 288, 74–91.
  - Bowler, N., C. E. Pierce, and A. W. Seed (2006), STEPS: A probabilistic rainfall forecasting scheme which merges an extrapolation nowcast with downscaled NWP, Q. J. R. Meteorol. Soc., 132, 2127–2155.
  - Foresti, L. and A. W. Seed (in press). On the spatial distribution of rainfall nowcasting errors due to orographic forcing. Meteorological Applications.

Computational time

Generation of the stochastic noise cascade with FFT is slow

More important to have higher resolution or large ensembles?

Rainfall not predictable at 500 m^2 at 5 minute resolution

Grid	Resolution [km]	Nr. members	Nr. lead times	Time [minutes]	
256x256	2	1	36	0.1	
256x256	2	5	36	0.6	
256x256	2	10	36	1.2	
256x256	2	20	36	2.4	
256x256	2	40	36	4.9	
256x256	2	10	6	0.3	
256x256	2	10	12	0.5	
256x256	2	10	24	0.9	
256x256	2	10	36	1.2	
256x256	2	10	48	1.6	Mult. factor upscaling
512x512	1	1	36	0.5	5.0
512x512	1	5	36	2.2	3.7
512x512	1	10	36	4.2	3.5
512x512	1	20	36	8.3	3.5
512x512	1	40	36	18.2	3.7
1024x1024	0.5	1	36	2.2	4.4
1024x1024	0.5	5	36	9.5	4.3
1024x1024	0.5	10	36	22.6	5.3 (7-9 GB mem)
1024x1024	0.5	20	36	45	estimation
1024x1024	0.5	40	36	90	estimation (100 thorin)